When do stock futures dominate price discovery?

Nidhi Aggarwal
Susan Thomas*
Indira Gandhi Institute of Development Research

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Abstract

Stock futures offer leveraged positions and are expected to attract informed traders. However, many researchers have found that the information share of the stock futures is surprisingly small, while the spot market appears to play a large role in price discovery. This paper investigates this phenomenon and offer two findings. First, liquidity of single stock futures plays a major role in influencing the price discovery. Securities where the spot market plays a major role tend to be those with illiquid single stock futures. High transactions costs appear to counterbalance the gains from leveraged trading. Second, during periods of high information flows, the stock futures appear to have a more important role. At such times, higher returns magnified by leverage appear to counterbalance transactions costs. These findings augment our understanding of the role of spot and futures markets in price discovery.

*Email: `susant@igidr.ac.in`, URL `http://www.igidr.ac.in/faculty/susant/`
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Contents

1 Introduction

When a security trades on multiple venues, there is great interest in understanding the role of these venues in price discovery. The literature has proposed a variety of ideas on how the role of these venues in price discovery can be measured.

When an informed trader places an order, leveraged positions on the derivatives market yield magnified returns. This leads to a presumption that derivatives markets play a major role in price discovery. The empirical literature has found that this is the case with index futures. But when faced with individual stocks, many contradictory results have been found.

In this paper, we explore this problem in greater depth, using data from India's National Stock Exchange, one of the world's largest exchanges with trading in single stock futures (SSFs). This presents a clean setting where both spot and futures are traded on the same exchange, and the futures are cash settled. With a large and active SSF market, we would expect the SSFs to play an important role in price discovery.

Our first finding is that, as with the mainstream literature, the overall summary statistics suggest that the futures and the spot markets have roughly equal information share. There is no clear domination of the futures market.

We pursue two hypotheses in investigating this problem further. First, we explore the consequences of cross-sectional variation in futures liquidity. For many stocks, the futures are relatively illiquid, which implies significant transactions costs for speculators and arbitrageurs who use these contracts. Therefore, informed traders may favour the spot market over the SSF market, even though the SSF markets offer higher returns through higher leverage.

Our empirical work reveals that the information share of the futures market is strong for highly liquid stock futures, but not for relatively illiquid stock futures. Transactions costs faced in futures trading thus work as sand in the wheels of price discovery, moving informed traders off to the spot market.

The second dimension that we explore is that of time-varying patterns in price discovery. We conjecture that there are certain times when large price movements are expected, driven by an inflow of news and information, that the role of the futures market could be greater. From the perspective of the informed trader who expects a certain return from a change in the market price in reaction to news, the SSF market would deliver the same returns through the multiple determined by the extent of the leverage.

Thus, the possibility of making higher gains during such news-intensive times, would motivate the informed trader to prefer the the futures market over the spot market. This would only happen if the gains from using the leveraged futures are large enough to compensate for the higher transactions costs of these markets.

We empirically test this by identifing news intensive periods and analysing the behaviour of price discovery between SSF and spot markets during these periods, and comparing these with periods of normal news. We identify news intensive periods as synonymous with periods of high volatility such as is seen during the opening of the market, and around periods of earnings announcements for specific companies. In both these situations, we find a greater role for the SSF compared with spot in price discovery.

The contribution of this paper lies in obtaining fresh insights into the puzzling finding in the literature, that the equity spot market is surprisingly important in price discovery. Our results suggest that while this result is a good description of the overall average behaviour, this is driven by a combination of transactions costs on the futures market and the price volatility. When the market is relatively liquid, and when price volatility is relatively large, the anomalous role of the equity spot market in price discovery largely subsides.

The paper starts with a presentation of the analysis of price discovery between leveraged and spot markets in Section 2, as well as the specific questions that we aim to focus on. Section 3 describes the research design and the estimation approach used. Details about the data used are in Section 4 with results in Section 5. We conclude the paper in Section 6.

2 Issues in price discovery and leveraged trading

When informed traders face the choice between sending orders to a spot or a derivatives market, we expect them to favour the magnified return that the leveraged market offers. Hence, we expect the derivatives market to dominate price discovery. The empirical literature on price discovery between derivatives and spot markets contradicts this simple picture. It reveals mixed results: while the derivatives often dominate price discovery, this is not always the case.

A large literature has examined price discovery between the spot index and index futures. Here, there is a broad consensus that information flows from the index futures to the index spot prices (Kawaller *et al.*, 1987; Stoll and Whaley, 1990; Chan, 1992; Fleming *et al.*, 1996; Pizzi *et al.*, 1998; Booth *et al.*, 1999; Tse, 1999). This result has held when analysing recent index products such as Exchange Traded Funds (ETFs) and E-mini contracts in price discovery as well (Hasbrouck, 2003; Kurov and Lasser, 2004; Tse *et al.*, 2006).

Contradictory results obtain, however, when analysing price discovery between index options and spot. Fleming *et al.* (1996) studied both futures and options contracts on the S & P 500, and concluded that futures lead the options, and options lead the spot. However, others found that index options lag the spot index (Booth *et al.*, 1999; Chiang and Fong, 2001). A key idea that emerged here was that the dominance of spot over options market in price discovery was primarily attributed to the options markets having *lower liquidity* than the spot market.

The question of price discovery across spot or derivatives markets is relatively clouded when dealing with a stock market index, given the relative complexity of placing basket trades for the index. This may generate an incentive to favour trading on the index derivatives. In addition, non-synchronous trading of index components induces positive autocorrelations in the index, which introduces complexities in measurement of price discovery. A cleaner setting is found with single stock futures, where neither of these two issues is faced.[1] The single stock futures (SSF) is a traded product with a clearly

[1]In addition to the literature on price discovery with index futures and single stock

observed price, as is the underlying spot market. Achieving a position on either the spot or the futures is a simple matter of placing a single order.

The SSF market is hence an interesting situation where insights can be obtained into the role of spot and futures markets in price discovery. Here, the broad finding of the literature is that the *spot* market tends to dominate price discovery. Shastri *et al.* (2008) investigated price discovery for securities listed on NYSE and NASDAQ that have exchange traded SSF contracts traded on the OneChicago exchange. SSFs were found to account for only about 24% of the price discovery, even when futures markets had both higher volumes and lower spreads compared to the underlying market.

In this paper, we explore this apparently anomalous result. Why do informed traders prefer to use the spot market? We focus on the the problem of illiquidity of the SSFs. While the futures offer leverage, they can be less liquid.[2]

The cost structure faced by a speculator trading the SSF versus the spot is:

$$(\mathrm{M} \times \mathrm{F}) \text{ versus } \mathrm{S}$$

where F, S are the futures and spot market prices, $F = Se^{rT}$. In the trading choices of the speculator, the costs of capital involved are either (M $\times$ F), the margin a trader must deposit with the clearing corporation to take the futures position and is a fraction of the price, or S which is the price of the share. If both futures and spot markets had perfect liquidity, speculators would always choose to trade in the leveraged markets. However, transactions costs change this comparison to:

$$(\mathrm{M}\ \mathrm{S}e^{rt} + 2 \times \mathrm{IC}_F) \text{ versus } (\mathrm{S} + 2 \times \mathrm{IC}_S)$$

futures, one additional dimension that the literature has explored is options on single stocks. Stephan and Whaley (1990); Chan *et al.* (1993) studied single security and security options market price at high frequencies and found that the spot leads the options, in both price discovery and trading activity, contrary to earlier studies (Manaster and Rendleman, 1982; Bhattacharya, 1987; Anthony, 1988). Chakravarty *et al.* (2004) found that the spot prices dominated options prices. However, they report that the options market tended to become more informative when trading volume was higher, and effective spreads are low in the options market.

[2] An example of a trade-off between illiquidity and leverage was modelled in the context of how informed traders behave while using options in trading strategies (Charlebois and Sapp, 2007).

where IC_F, IC_S are the price impact cost paid for the futures and spot market trade as market liquidity cost.[3] The price impact cost has to be paid twice – once at the trade to enter the position, and the other at exit. In the best case, these price impact costs are a very small fraction of the transaction value.

This suggests that when the futures are highly liquid, the leverage will attract informed traders. But when futures liquidity is weak, informed traders may prefer transactions on the spot market despite the lack of leverage.

Another dimension that may shape the role in price discovery is that of the flow of news and information. When news comes into the market, the changes in prices are likely high enough that the benefits of leverage override the costs of transactions when trading futures. This could motivate informed traders and speculators towards a greater use of futures rather than spot markets. This may imply that price discovery exists between two-states, where the spot market is the preferred venue for price discovery in tranquil times, but the futures market comes into a dominant role when there is high volatility.

From these perspectives, the questions that is posed in this paper are:

1. What is the role of single stock futures in price discovery?
2. How does this role vary with the liquidity of the single stock futures?
3. Is there a variation in the role of stock futures in price discovery based on the the flow of news and price volatility?

[3]This is a relatively simplistic view of the costs in the trade-off between spot and SSF contracts. In reality, the trader could face a different cost of capital for the margin payment compared to that for the spot transaction, where the security can be deposited as collateral. If the trader holds the position upto the maturity of the SSF contract, then the liquidity cost will be IC_F rather than $2\times\mathrm{IC}_F$. If the trader holds the position for longer than the maturity of the SSF contract, there is the additional cost of the rollover from contract to contract. This calls for a more detailed model of transaction costs in trading which we leave for another paper. The simple model above is only used to illustrate the trade-off between illiquidity costs and costs of capital.

Table 1 Top derivatives exchanges for single stock futures contracts, 2010

Data from World Federation of Exchanges (WFE) website for the top five exchanges in the world, by number of SSF contracts traded.

	Number of SSF contracts traded (in millions)			
Rank	Exchange	2008	2009	2010
1	NYSE Liffe Europe	124	166	291
2	NSE India	226	161	176
3	EUREX	130	114	151
4	Johannesburg Stock Exchange	420	89	79
5	KOREA Exchange	12	37	45

3 Methodology

3.1 Institutional setting

The analysis is carried out in the relatively unique setting of SSF trading at the National Stock Exchange (NSE), in India. India is one of the few countries where the SSF market has been highly successful[4]. As Table 1 shows, NSE has consistently been among the world's largest exchanges in this regard. This is hence a good setting for the analysis of the relationship between the spot and the futures market for single stocks.

There are two previous papers on price discovery in the Indian SSF market. Kumar and Tse (2009) analysed data on 30 securities trading on NSE during 2004, and Kumar and Chaturvedla (2007) examined a set of 46 securities using high frequency data.[5] Kumar and Tse (2009) used both order book data as well as trades data. They found that the spot market dominated price discovery compared to the futures market when they used trade data. But the reverse was true when they used order book price data.

Kumar and Chaturvedla (2007) found that, on average, the share of futures market in the price discovery process at high frequencies stood at around 36%. They explain the lack of dominance of price discovery in the futures

[4] *"Indian Bourse ousts JSE as largest single stock futures market"* Bloomberg (April 2009)

[5] Kumar and Tse (2009) used data at a frequency of one minute, while Kumar and Chaturvedla (2007) used prices at frequencies of one-minute and five-minutes.

markets to the absence of a strong institutional trading presence.[6] Neither paper explicitly focusses on the question of the trade-off between liquidity and leverage in the price discovery process.

3.2 Estimation strategy

Our approach in this paper is to focus on securities that have robust liquidity in both the SSF as well as in the underlying spot markets. The next step is to create subsets of securities that have more liquidity in SSF compared to the spot markets, and vice versa. The selection of securities that are liquid is based on two alternative sources of liquidity (discussed in greater detail in section 3.2.1):

1. *Traded volumes:* which is a *post-trade* liquidity measure that has the advantage of having been used widely in the literature. This is measured either in number of shares traded or in value traded.
2. *Price impact cost:* which is the potential increment in price over the bid-ask price at which an order at a fixed size will be executed. This is a *pre-trade* liquidity measure that captures the liquidity part of transactions costs.

It is anticipated that securities that have good pre-trade liquidity will also be the ones that have good post-trade liquidity. Once the first sample of liquid securities are identified, subsets of securities according to liquidity are done using these same measures. The price discovery between SSF and spot will then be estimated and tested for the overall sample, as well as for the subsets separately. Our hypothesis is that when the futures market is more liquid than the spot market, the futures market will dominate price discovery. We also hypothesise that the reverse is true.

$$H_0 : (\text{Price discovery}_F > \text{Price discovery}_S) \text{ if } (\text{Liquidity}_F > \text{Liquidity}_S)$$
$$H_0 : (\text{Price discovery}_F < \text{Price discovery}_S) \text{ if } (\text{Liquidity}_F < \text{Liquidity}_S)$$

[6] They report that only 11% of the trading volumes in the Indian equity markets are from institutional traders.

We then nuance the importance of market liquidity in price discovery by trying to identify periods when information flow into the market is likely to be high. We do this by testing the price discovery *seperately* during periods of high and low volatility. If large price movements are envisaged by the informed trader based on new information, then this may pay for the enhanced transactions costs of the futures. We hypothesise that under such situations of high market volatility, futures markets will play a greater role in price discovery even for securities where futures markets are typically less liquid than the spot.

$$H_0 : (\text{Price discovery}_{(\text{F, high } \sigma)}) > (\text{Price discovery}_{(\text{F, low } \sigma)})$$
$$H_A : (\text{Price discovery}_{(\text{F, high } \sigma)}) < (\text{Price discovery}_{(\text{F, low } \sigma)})$$

For this purpose, we identify periods of high volatility in the market in two ways:

1. **Market-wide volatility**: During the opening of the market, when we expect higher market volatility due to the overnight news flow.

   Upto October 2010, the Indian equity markets did not have a pre-open auction mechanism through which the opening price could be discovered. Instead, trading opened directly into the continuous market. This meant that the market returns showed high volatility at the start, which persisted for nearly half an hour after market open.

   We focus on the period before the start of the pre-open auction mechanism and test for price discovery separately in the first half an hour period *post market open*, and the remaining period after. We hypothesise that the fraction of price discovery attributable to futures markets would be higher in the period immediately after market open across all securities, compared to the fraction in the remaining period.

2. **Security specific volatility**: The previous strategy identifies the role of futures under conditions of high stock volatility, regardless of the source of this volatility. However, overall market volatility is comprised of market-wide news and stock-specific news. The futures may play a bigger role when there is stock-specific news, as opposed to times when there is market-wide news.

> In order to identify security-specific news events, we identify days on which earnings are announced for securities. We isolate a period immediately after the announcement. Traders who get the information first are likely to trade in the leveraged contracts more than they would compared to when there is no news. We hypothesise that there will be a greater share of futures in price discovery when there is substantial stock-specific news.

3.2.1 Liquidity measurement

We improve upon existing research in the price discovery literature by incorporating explicit measures of market liquidity into the research design in order to understand how liquidity affects price discovery across markets.

Fleming *et al.* (1996) examined the effect of liquidity and trading costs, measured as absolute spreads and traded volumes. Traded volumes are an outcome of the trading process and do not measure transactions costs. The absolute spread is a pre-trade measure, but is typically limited to the smallest trade size, while trades contributing to the price discovery process are likely to have varying sizes in different markets, particularly across leveraged markets where a larger position can be taken compared to spot markets.

In comparison to the traded volumes/absolute spread, we argue that the price impact cost measure is a better input to understanding how liquidity influences price discovery, since traders will take the transactions costs of liquidity to calculate the net returns of the trade before placing the order to trade. Therefore, we use price impact cost as the liquidity measure to differentiate one security from another.

Trading on the Indian equity markets takes place through an anonymous electronic limit order book market where all traders can see the limit order book. Traders can estimate price impact cost before a trade is placed. Since we have access to the limit order book information for both futures and the spot markets, we are able to measure market liquidity directly by calculating the price impact cost cost of a given trade from the available limit orders waiting to be executed. This allows us to explicitly measure pre-trade liquidity.

Further, we can standardise the price paid/received for the same order size whether it is in the futures or the spot market. If there is a liquidity premium to larger size transactions, access to the limit order book information can be used to ensure that we are using the correct futures and spot price while testing for price discovery between the two.

3.2.2 Measuring price discovery

The modern literature on measuring price discovery began with Hasbrouck (1995). This paper proposed using the cointegration framework, where market prices are decomposed into a random walk component (common to both market prices) and a transient component (attributable to market liquidity) specific to a particular market. The random walk component represented the implicit efficient price of the security, whose variation could be used to measure the contribution of each market to price discovery, and was called the *information share* (IS) of the market. Another commonly used alternative is the component share (CS) approach proposed by Booth *et al.* (1999); Chu *et al.* (1999); Baillie *et al.* (2002) that was built on the permanent-transitory component decomposition of Gonzalo and Granger (1995).

Both approaches use the concept of *implicit efficient price* contained in the price of security, and have been used extensively in the literature (Huang, 2002; Chakravarty *et al.*, 2004; Hendershott and Jones, 2005; Kurov and Lasser, 2004; Anand and Subhramanyam, 2008). However, there has been substantial debate in the literature as to what each measure implies for price discovery, and under what conditions both measures identify similar dominance in price discovery.[7] Lehmann (2002) suggests that these difficulties are unsurprising because both the approaches are based on the *reduced form* vector error correction model errors, while the role of price discovery depends on the parameters of the structural model.

In a bid to clear this confusion, Yan and Zivot (2010) proposed a structural cointegration model for the price changes in multiple market. The paper interprets the IS and CS measures in terms of two underlying structural innovations: *information related innovations* (permanent shocks) due to the arrival of news and *non-information related innovations* (transitory shocks)

[7] A lot of examples based on simple microstructure models were constructed (Hasbrouck, 2002; Harris *et al.*, 2002; Baillie *et al.*, 2002; deJong, 2002) to do a comparative analysis of the IS and CS measures. This literature has raised questions about the correct interpretation of each of these measures.

such as those due to trading frictions. The paper notes that while both the IS and CS adjust for the *relative* avoidance of noise trading/pure market liquidity shocks, the IS can provide information on the relative informativeness of individual markets.[8]

The paper demonstrates that in a two-market framework, CS of Market 1 will be higher than that of Market 2, if Market 2 responds more strongly to the transitory shock than Market 1. On the other hand, the IS of Market 1 could be higher if it incorporates more new information *and/or* impounds less liquidity shocks. That is, high values of IS for Market 1 due to a strong response of Market 1 to new information cannot be distinguished from a high value of IS in Market 1 due to a strong response of Market 2 to frictions. In such a scenario, making inferences on which market dominates the price discovery process just on the basis of high IS values could be misleading. The paper suggests the joint use of the CS and IS to sort out the confounding effects of both these shocks.

Keeping in consideration this strand of literature, in this paper, we use Hasbrouck's methodology to estimate IS and use CS and our measure of transitory shocks to supplement our inferences from the IS estimates.

We take care of the Yan and Zivot (2010) concern on the proper inference of IS using the following two ways:

1. We hypothesize that the transitory shocks in both markets can be proxied by the quality of market liquidity, which can be measured explicitly as a cost in terms of the price impact (IC) of a given transaction size (Q):

$$\mathrm{IC}_t = P_{Q,t} - P_{\mathrm{midquote},t}/P_{\mathrm{midquote},t}$$

   where $P_{Q,t}$ is the price per unit share paid for a transaction size of Q at time t. When information arrives in the market place at $(t+1)$, both the P_{midquote} as well as P_Q would adjust to incorporate the information. Returns measured as change in $P_{Q,t}$ would be a combination of both information as well as the liquidity shock. The change in the IC, on the other hand, is likely to capture the pure liquidity effects, since it inherently adjusts the changes in P_Q (which will incorporate both information and liquidity changes) for

[8] Yan and Zivot (2010) structural decomposition of the two measures suggests that while IS consists of contemporaneous responses to both permanent and transitory shocks, of each market, CS involves the structural parameters involving price responses only to the frictional innovations.

changes in P_{midquote} (which will incorporate mostly information changes). Therefore, IC could be a credible proxy for transitory shocks in a market.

The advantage with the electronic LOB market is that intra-day IC at various transaction sizes Q can be directly observed for both the futures and spot markets, since the LOB is available at multiple points during the day. This can be used to calculate the variance of impact cost at fixed Q, which can then be used as an exogenous measure of the transitory shocks presented in Yan and Zivot (2010) to make a robust inference about the dominance of price discovery.

If a market *simultaneously* shows a higher IS *and* a lower variance of impact cost (ie, the transitory shock proxy) compared to the other market, it supports the argument for robust price discovery dominance.

2. A ratio of IS and CS can be used to meaure the relative impact of permanent shocks, where Market 1 is the SSF market (F) and Market 2 is the spot market (S):

$$\frac{|IS_F \times CS_S|}{|IS_S \times CS_F|} = \frac{|d^P_{0,F}|}{|d^P_{0,S}|}$$

where $d^P_{0,F}$ measures the contemporaneous response of the SSF market to permanent shocks and $d^P_{0,S}$ measures the same for the spot market. If the value of the ratio is greater than 1, then it would appear that the SSF market is more responsive to permanent shocks than the spot market. Thus, this ratio can be used to infer which market is more responsive to the new information shocks.

4 Data description

The Indian equities market offer a unique setting to study price discovery between SSF and underying spot markets. Some features that stand out are:

Microstructure Both spot as well as the derivatives markets trade simultaneously on the same exchange. Derivatives market liquidity is concentrated in one exchange[9] though the spot market trading is more spread across the

[9]Indian securities market, a review (ISMR) - 2009 http://www.nseindia.com/content/us/ismr_full2009.pdf.

two primary equity exchanges in the country.[10] This yields high quality data and the lack of confounding effects particularly when dealing with ultra high frequency data. Trading is done through an anonymous, electronic limit order-driven market with price-time priority on the orders placed during the trading day. Trading hours are between 9am and 3:30pm.

Around 1400 securities listed and traded on the NSE, out of which 223 securities have derivatives contract on them. For a frame of reference, the average daily turnover in the equity derivatives market of NSE during 2010-2011 has been about $21 billion which is around twelve times the turnover on the overall spot market.

Transparency Information about trades, quotes, and quantities are disseminated by the exchange on a real time basis. At any point of time, market participants can view the best five bid-ask quotes available for the spot as well as the derivatives markets. These quotes are updated in real-time on the screens at the trading member terminals and with a short lag on public avenues like the internet.

The ability to see the best five available quotes on both side of the limit order book enables traders to have an accurate price at which a trade is likely to be executed. This is a measure of market liquidity that span various trade sizes, according to the requirement of the trader. For a frame of reference, the average price impact cost of a spot index trade of Rs. 5 million (USD 100,000) in 2009 was 0.09% while the same for the near month index futures was 0.015%.

We focus on a set of the most liquid securities that trade at the NSE, which also have related futures and options trading actively. We identify and use data on 97 securities and their related near-month futures contract, for a period of March 2009 to August 2009. During this period, the market share of the futures contracts on these 97 securities comprised 82% of the total market volumes, while they accounted for 51% of the volumes on the spot market by number of contracts/shares traded.[11]

The period of the sample covers 114 trading days. However, we exclude two days to expiration of the near month futures trading each month since the price efficiency and liquidity of the contracts are extremely volatile around

[10]The second of these is the Bombay Stock Exchange.
[11]*Source*: NSE India

these. This leaves us with 102 trading days in the sample. This yields a large dataset with 9,894 days of intra-day data for spot and SSF trading.

For each of these securities, we observe the intra-day traded prices, as well as the limit order book information for both the futures and the spot contracts. We use the mid-quote prices for both the futures and the spot markets. This exploits the fact that traders can update orders in the limit order book market to reflect new information which likely leads traded prices that are naturally updated later.

We also collect data on the two measures for the liquidity described in section 3.2.1 of both spot and futures as an input to our analysis. We next synchronise the data on two dimensions:

Frequency Price synchronisation on frequency is a standard problem that has to be dealt with in all high-frequency analysis. We synchronise the data at 1-second frequency and use it to estimate the information share of each market. As suggested by Hasbrouck (1995), the advantage of using 1 second frequency is exposition of the sequential operation of the market enabling IS to accurately measure who moves first in the process of price discovey. Sampling at lower frequencies results in this information loss and also causes high contmeporaneous correlation in the residuals between the markets created due to time aggregation.[12]

Size of trade The second dimension of synchronisation is of order size at which to calculate the price impact measure. This is not typically dealt with in the standard literature, because the limit order book for securities are not frequently observed. Since our work focusses on identifying the impact of liquidity on the price discovery process, we need to standardise the observed liquidity costs to some fixed transaction size. However, the equity spot market in India trades at a market lot size of one share while the market lot of a futures contract, on the other hand, can vary as exposures of 10 to 15000 shares depending upon the price level of the security. We choose to calculate the price impact cost measures at a trade size of Rs. 250,000 (around USD 5600).[13]

[12]We had also estimated IS at lower frequecies (5-minute, 1-minute, 30-seconds, 15-seconds). However, estimation at all these frequencies resulted in wide IS bands, the part of cause of which lies in the high contemporaneous correlation in the residuals caused due to time aggregation

[13]We analyse the trades data for what is the average size of trades that take place in

Figure 1 Illustrative intra-day graphs of futures and spot prices and liquidity

The first row shows the one-minute mid-quote prices and the market impact cost (IC) for a high liquidity security (RELIANCE) on the spot and the futures market plotted for a representative day (13^{th} July 2009). The second row shows the two graphs for a low liquidity security (CORPBANK).
IC is calculated at a one-minute frequency for an order size of Rs 250,000 which corresponds to the average transaction size on the futures market.

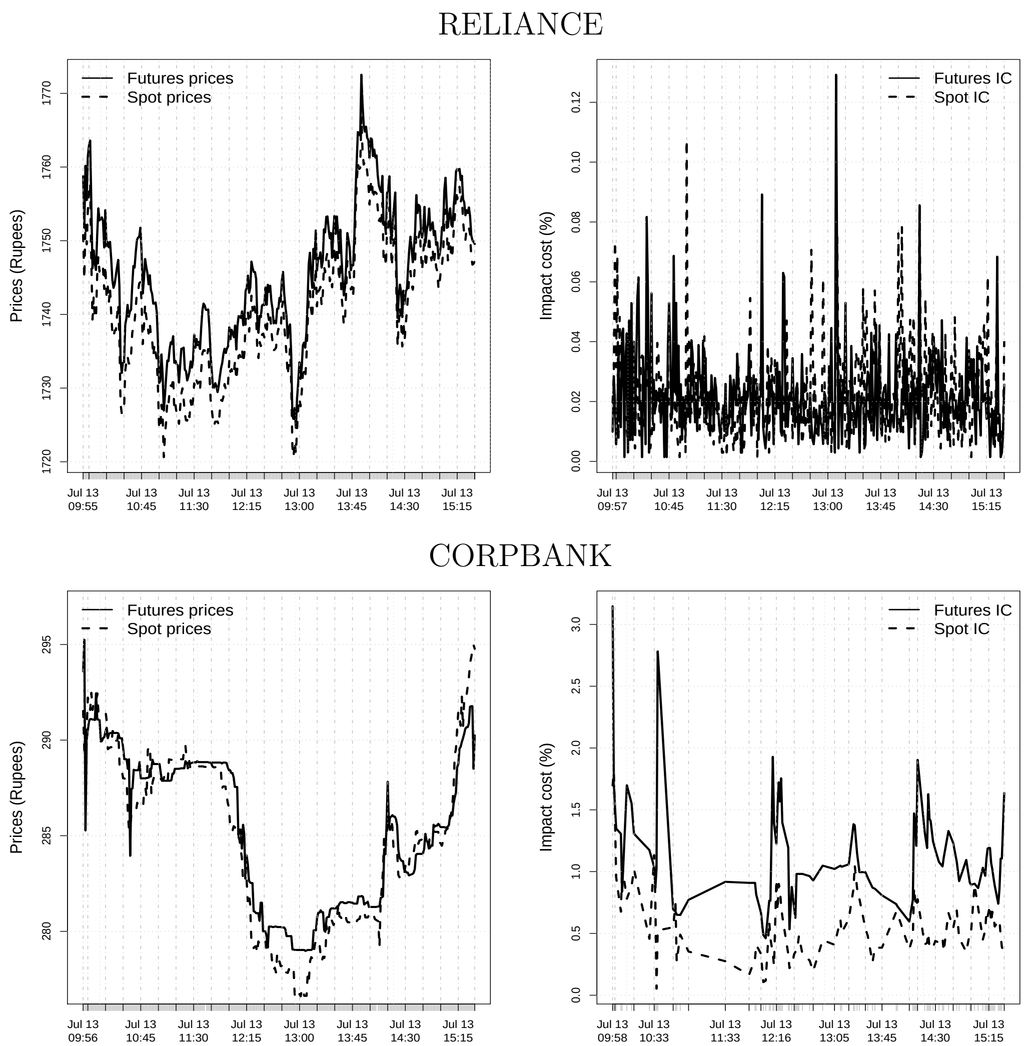

Table 2 Liquidity characteristics of the full sample

The tabled numbers are averages across the data for the 97 securities in the sample. Both the bid-ask spread and the price impact cost are calculated with respect to the *benchmark price*, which is the midquote price between the best bid and ask prices in the LOB. The price impact cost has been calculated at Rs.250,000 for both the futures and the spot market for each security. The median price impact cost for each security is then averaged for the sample.
Both the returns and the price impact cost volatility numbers have been annualised.

	Full sample	
	SSF	Spot
Volumes ('000 shares)	6,337	5,267
Bid-ask spread (%)	0.56	0.11
Price impact cost, IC (%)	0.24	0.13
Price impact cost volatility, σ_{IC} (%)	3.10	2.02
Returns volatility (%)	51.88	50.53

> To illustrate the behaviour of liquidity of securities in the sample, Figure 1 shows the intra-day mid-quote prices and pre-trade liquidity price impact cost for the most liquid security (RELIANCE) and the least liquid security (CORPORATION BANK) in the sample for a representative day. The graphs show that futures and spot prices of the liquid security are tightly linked continuously during the trading day. The less liquid security has futures prices that are less responsive in comparison to the spot in real-time. Similarly, the pre-trade liquidity measure of impact cost in the futures and spot markets are similar for the most liquid security (at around 2.5 basis points). But for the less liquid security, the futures market has much lower liquidity (impact cost of around 125 basis points) compared to that of the spot market (impact cost of around 45 basis points).

Table 2 presents some summary statistics for the liquidity of the selected sample, for both spot and futures markets. These include traded volumes (in terms of number of shares/contracts traded), average values of the bid-ask spread (as a percentage of the mid-quote price) and the price impact cost (which is the increase in price above the mid-quote price incurred for a trade

the each market separately. In the universe of securities that we have chosen, the average transaction size for the futures markets turns out to be Rs 250,000 while that in the spot market works out to be one-tenth that size. Therefore, we standardised the analysis at transaction sizes of Rs 250,000.

Table 3 Liquidity characteristics for quartiles by traded volume

The original sample of 97 securities are broken into quartiles Q1−Q4 by traded volumes. Q1 is the quartile with the most liquid securities, or those with the highest traded volume during the sample period. Q4 is the set of securities with the least liquidity or lowest traded volume/highest impact cost.
The measures presented below has been calculated similar to those in Table 2, except for ΔIC(futures-spot) which is the average difference between the price impact cost on the futures and the spot market for the securities in that quartile.
The numbers in boldface are where the futures markets values are significantly different from the spot market values at a 5% confidence level.

	Q1		Q2		Q3		Q4	
	Futures	Spot	Futures	Spot	Futures	Spot	Futures	Spot
Volumes ('000 shares)	9707	7846	9529	8405	5337	3940	634	770
Spread (%)	**0.11**	0.05	**0.15**	0.07	**0.28**	0.11	**1.74**	0.23
IC (%)	0.04	0.04	**0.07**	0.06	**0.13**	0.11	**0.74**	0.29
$\Delta IC_{\text{(Futures - Spot)}}$	0.00		0.01		0.02		0.45	
σ_{IC} (%)	0.45	0.54	0.75	0.83	**1.61**	1.63	**9.68**	5.14
σ_{returns} (%)	50	49	54	53	52	51	52	48

of size of Rs.250,000). This shows that the futures has higher post-trade liquidity in terms of higher traded volumes, but the spot market has better pre-trade liquidity in terms of both the average spread and the average price impact cost. The table also shows the returns volatility of the securities in the sample and the volatility of the price impact cost (at the same transaction size).

In order to explore cross-sectional variation, the full sample is then broken into quartiles Q1-Q4, with securities sorted by decreasing pre-trade liquidity (or increasing price impact costs).[14] Q1 has the most liquid, and Q4 has the least liquid securities.

[14]We created quartiles both by traded volumes and by price impact costs of the securities, in both the spot and futures markets. Q4 consistently had lower average traded volumes in the futures market compared to spot. All other quartiles had greater volumes in their futures contracts. The summary statistics of the quartiles had a similar pattern for the bid-ask spread, price impact cost and volatility, for both sets of quartiles. The identity of the securities in the two sets of quartiles differ little across the two categorisations. We also present the summary statistics for the quartiles by price impact cost in the Appendix.

Table 4 Average IS results for quartiles based on traded volumes

The numbers in the table show the Information Share (IS) for first the futures, IS_F, and then the spot market, IS_S, for the entire sample period. Each IS estimate is presented as a set of three values: *Max* which is the upper bound from the IS estimation, *Min* which is the lower bound, and *Mean* which is average of *Max* and *Min* for that market. The IS for one market is calculated as (1 - IS) for the other market.
The values marked in boldface indicate when the mean IS_F is significantly different from IS_S at a 1% level of confidence.

	IS_F			IS_S		
	Max	Min	Mean	Max	Min	Mean
Full sample	0.52	0.46	0.49	0.54	0.48	0.51
Turnover quartiles:						
Q1	0.69	0.59	**0.64**	0.41	0.31	0.36
Q2	0.63	0.55	**0.59**	0.45	0.37	0.41
Q3	0.53	0.48	0.51	0.52	0.47	0.50
Q4	0.26	0.24	0.25	0.76	0.74	**0.75**

Similar summary statistics for average post-trade and pre-trade liquidity are presented for Q1-Q4 in Table 3. In contrast to the full sample liquidity between SSF and spot, where spot is more liquid than futures in pre-trade liquidity, the most liquid quartile (Q1) securities have similar futures and spot market pre-trade liquidity. However, the *futures pre-trade* liquidity is significantly worse than the *spot market pre-trade* liquidity for the securities that have lower liquidity (Q4). The variance of pre-trade liquidity is also much wider for these low liquidity securities.

These tables and graphs support the notion that (a) liquidity does vary significantly, even among the most liquid securities, and (b) despite the advantage of leverage, the spot market often has the advantage of lower transactions cost.

5 Results

The Hasbrouck (1995) IS is estimated using intra-day data at a frequency of one-second for each security. We summarise and present the estimated IS_F, IS_S as the sample average of the median daily value for each security, $i = 1 \ldots 97$. These are reported in Table 4 as the *Full Sample* results.

Table 5 Average IS estimates for quartiles based on price impact cost

The numbers in the table show first IS_F, and then IS_S, for Q1 (most liquid) and Q4 (least liquid) where the quartiles are based on decreasing order of liquidity (or increasing order of price impact cost).
The values marked in boldface indicates when the mean $\mathrm{IS_F}$ is significantly different from $\mathrm{IS_S}$, at a 5% level of significance.

	IS_F			IS_S		
	Max	Min	Mean	Max	Min	Mean
Q1	0.66	0.55	**0.61**	0.45	0.34	0.39
Q2	0.63	0.55	**0.59**	0.45	0.37	0.41
Q3	0.55	0.51	0.53	0.49	0.45	0.47
Q4	0.25	0.23	0.24	0.77	0.75	**0.76**

In addition, we also calculate the average for the four sub-samples, with Q1 being the securities with the largest traded volumes, and Q4 as those securities with the least.

We see that for the full sample, the average IS of each market turns out to be *not* significantly different from each other ($\mathrm{IS}_F = 49\%$ compared to $\mathrm{IS}_S = 51\%$) at a 95% confidence level. This is consistent with the results reported in other research on price discovery between the SSF and spot markets.

However, the estimated IS_F across post-trade liquidity quartiles (Traded Volumes) show striking differences. The futures have a dominant share in price discovery for securities in the more liquid quartiles. IS_F has an upper and lower bound significantly higher than 50% for both the Q1 and Q2 securities.

The IS_F declines below 50% for the least liquid securities. The average IS_F reduces remarkably to a mere 25% in the least liquid quartile (Q4).

Table 5 shows the information share of the two markets across liquidity quartiles based on price impact cost. Similar to the results in Table 4, the IS_F across price impact cost quartiles also declines from the most liquid to the least liquid quartile. Thus, the IS estimation results remain consistent across IC *and* traded volume quartiles. The basic result is thus robust to these two alternative approaches to measuring liquidity.

5.1 Variation in price discovery by liquidity

Section 3.2.2 showed how, starting from the original estimation framework of cointegration, the dominance by one market in price discovery can be linked back to how much of the reaction was to permanent shocks compared to transitory shocks. This will help us establish that the market that has high IS values also has lower exposure to transitory shocks. We propose doing this in two ways:

1. Use the price impact cost as a proxy measure of transitory shocks and test whether there is a relation between IS_F and these proxies, and
2. Formalise the (Yan and Zivot, 2010) suggestion of using both IS and CS measures together by creating a ratio – $(IS_F \times CS_S)/(IS_S \times CS_F)$ – and test whether this *IS-CS-Ratio* is greater than one for the market with higher IS_F.

Inference using proxies of transitory shocks

Figure 2 shows scatterplots of the relation between the information share of the futures market for a security i, $\text{IS}_{F,i}$ and the transitory shock proxy measures using liquidity of futures and spot markets. These measures are the ratio of the liquidity cost in the futures market versus the liquidity cost in the spot market, ICR_i, and the ratio of the volatility of liquidity costs in the futures versus the spot market, $\text{ICR}_{\sigma,i}$.

The graph suggests a strong negative relation between $\text{IS}_{F,i}$ and the ICR_i – the higher the ICR_i, lower is the IS_F or the information share in the futures market for the security. The second graph suggests a similar negative relation between $\text{IS}_{F,i}$ and the $\text{ICR}_{\sigma,i}$– the higher the volatility of liquidity in the futures market compared to spot, the less robust is the inference of high values of IS_F about the dominance of futures over spot in price discovery. We formally test this conjecture in a regression setup:

$$\log(\text{IS}_{F,i}) = \alpha + \beta_1 \text{ICR}_i + \epsilon_i$$

If the ratio of the cost of liquidity is a proxy for the effect of transitory shocks, then we would expect that the effect of the permanent shock in the form of high IS value is more robust. This implies that:

Figure 2 Security-wise IS_F vis-a-vis ICR and ICR_σ

The first graph is the scatterplot of the IS of the futures market (IS_F) vis-a-vis the ratio of the impact cost on the futures and spot market (ICR). A value of ICR greater than one indicates lesser liquidity on the futures market in comparison to the spot market.
The second graph shows the relationship between (IS_F) and the variance in liquidity in the futures and spot market (ICR_σ). A value of ICR_σ ratio 1 will suggest greater response of futures market to transitory shocks.

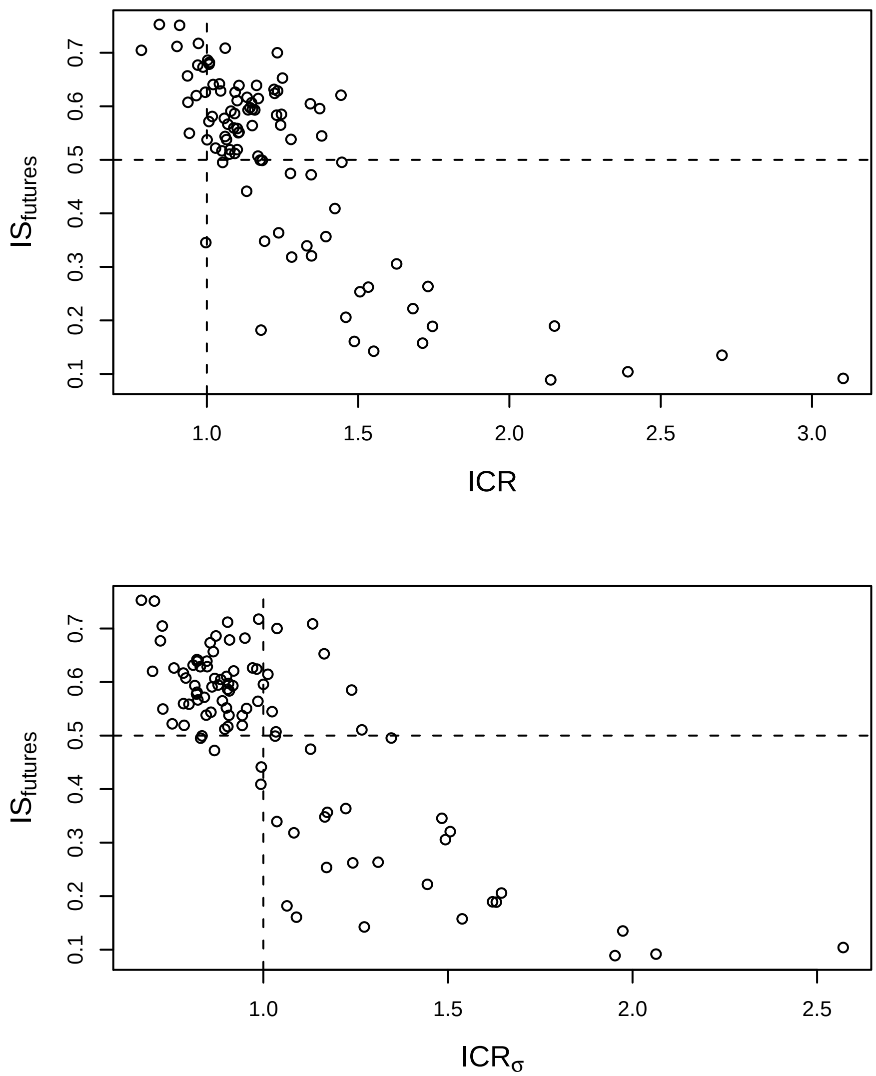

Table 6 Regression results of IS_F on ICR

The regression equation is

$$\log IS_{F,i} = \alpha + \beta_1 ICR_i + \epsilon_i$$

Where $IS_{F,i}$ is the average information share of the futures market for security i, ICR_i is the ratio of the price impact cost in the futures market to impact cost in spot market for i.

	Estimate	Std. Error	t-value	Pr(>|t|)
α	0.6495	0.1005	6.46	0.0000
$\hat{\beta}_1$	-1.1431	0.0773	-14.79	0.0000
Adjusted R^2	0.70			

$$H_0 : \beta_1 = 0$$
$$H_A : \beta_1 \neq 0$$

If the null is rejected, this would imply that the estimated IS_F and the liquidity costs are correlated, which then makes a more robust case for high estimates of IS_F.

Table 6 presents the regression results, which indicates that the null is rejected. On average across securities, the relationship between IS_F and the ratio of liquidity between the futures and spot markets is *negative*, implying that higher IS_F goes along with lower ratio of liquidity costs in futures market compared to spot market liquidity costs. This leads us to believe that higher estimated values of IS_F are robust indicators of dominance of futures markets in price discovery.

The second proxy measure for the presence of transitory shocks in a market for a particular security i is the ratio of the volatility of liquidity costs in futures versus the spot market ($ICR_{\sigma,i}$). A high value of ICR_σ ratio would suggest that market is more responsive to the transitory shocks. The regression model is:

$$\log(IS_{F,i}) = \alpha + \beta_1 ICR_{\sigma,i} + \epsilon_i$$

Similar to the first proxy for transitory shocks, we conduct the hypothesis

Table 7 Regression results of IS_F on ICR_σ

The regression equation is

$$\log IS_{F,i} = \alpha + \beta_1 ICR_{\sigma,i} + \epsilon_i$$

Where $\mathrm{IS}_{F,i}$ is the average information share of the futures market for security i, $\mathrm{ICR}_{\sigma,i}$ is the ratio of the price impact cost volatility in the futures market to impact cost volatility in spot market for i.

	Estimate	Std. Error	t value	Pr(>|t|)
α	0.5657	0.0914	6.19	0.0000
β_1	-1.2952	0.0840	-15.41	0.0000
R^2	0.72			

test:

$$\begin{aligned} H_0 &: \beta_1 = 0 \\ H_A &: \beta_1 \neq 0 \end{aligned}$$

Table 7 presents the regression results of $\mathrm{IS}_{F,i}$ on the ratio of the liquidity volatility in the two markets, and we find that the null is rejected here as well. The negative coefficient associated with the $\mathrm{ICR}_{\sigma,i}$ indicates greater the volatility of liquidity changes in the futures market in relation to the spot market, the lower would be the $\mathrm{IS}_{F,i}$ for the security. The result confirms with the Yan and Zivot (2010) observation that high values of IS_F estimates can be due to the a stronger response to market frictions in the spot (second) market.[15]

An interesting observation from the results above is that there appears to exist a liquidity threshold that influences the dominance of futures markets over spot markets in the price discovery process. When the futures market impact cost volatility is greater than the spot market impact cost volatility, there is a greater probability that $\mathrm{IS}_F < \mathrm{IS}_S$ ($N1$ of the sample). Likewise, when the futures market impact cost is greater than $1.3 \times$ the spot market impact cost, there is a greater probability that $\mathrm{IS}_F < \mathrm{IS}_S$. This would suggest

[15] To test if our results for higher IS in Q1 and Q2 are driven by the higher response of the futures market to permanent shocks or is it due to the higher resposne of the spot market to the transitory shocks, we use the IS-CS ratio proposed by Yan and Zivot (2010).

Table 8 IS and CS results based on IC quartiles

The numbers in the table indicate the average daily IS and CS value for the full sample. The last column uses the IS and CS collectively to determine which market is more responsive to the permanent shocks. This is also presented separately for the four quartiles by price impact cost.
The numbers in boldface indicate instances when the IS-CS ratios are significantly greater than 1 at a 5% level of significance. A value of the IS-CS ratio significantly greater than one will indicate that the futures market is more responsive to the permanent shocks, than the spot market. A value less than one will suggest otherwise.

	IS_F	IS_S	CS_F	CS_S	$\frac{\lvert \text{IS}_F \times \text{CS}_S \rvert}{\lvert \text{IS}_S \times \text{CS}_F \rvert}$
Full Sample	0.49	0.51	0.50	0.50	1.00
Q1	0.61	0.39	0.58	0.42	**1.14**
Q2	0.59	0.41	0.56	0.44	**1.13**
Q3	0.53	0.47	0.52	0.48	1.06
Q4	0.24	0.76	0.32	0.68	0.68

that the cost of leverage compensates for at least 30% of the disadvantage of illiquidity in the Indian equities market.

Inference using the IS-CS-ratio

Table 8 presents the IS and CS estimates for the two markets, for the full sample as well as different quartiles. The table also shows the IS-CS ratio from Section 3.2.2 for the futures market in each case.

As in the previous tables, there is no dominant market for price discovery averaged across full sample. However, when viewed using liquidity quartiles, futures appear to dominate price discovery for securities in the top quartiles by liquidity (Q1 and Q2), while the spot market appears to dominate for the quartile with the lowest liquidity in the futures market.[16]

Thus, the results from our estimations is that the average IS_F appears to show that neither market dominates the price discovery process for the full sample. However, a closer look at the IS_F and IS_S for individual securities

[16]The results of the IS-CS ratio strengthen the argument that while for the full sample, neither of the market seem to be dominating the price discovery process, the high values of IS in Q1 and Q2 is not due to the greater responsiveness of the spot market to the transitory shocks, but is due to the higher responsiveness of the futures market to the permanent shocks.

tell a different story. Futures markets do dominate price discovery over spot markets, once the futures market is adequately liquid.

When the liquidity of the futures market is relatively worse than that of the spot market, the spot market dominates price discovery. Since price discovery is driven by choices made by speculators and arbitrageurs of where to trade information, this relation between price discovery dominance and liquidity appears to validate the hypothesis of a trade-off between the cost of capital and the cost of transacting. When the high cost of illiquidity in futures markets completely offsets the advantage of low cost of capital in futures (as in the case of the Q4 securities), price discovery shifts to being dominated by the spot market.

5.2 Variation in price discovery by information

Another situation where such a trade-off assumes greater importance is when news and information comes to market. There are multiple reasons for traders to prefer trading futures when news and information into the market is anticipated. When information flow into the market is high, leverage enables the speculator to get a higher return on the same information. In addition, the Indian equity SSF markets are cash-settled, making futures operationally easier to trade compared to the spot.

In such situations, traders ought to prefer trading in SSF over the spot market, even if they perceive that the SSF markets have a higher illiquidity premium. We test this in two instances of information flows into the market:

1. Periods of high market wide information – which is captured as periods of broad market volatility at market open.
2. Periods of high security specific information – which is captured as periods when the security-specific information flows are large.

In either of these cases, the hypothesis is that IS_F is likely to be higher during such periods than during other periods where volatility is more typical.

Table 9 Intra-day features of IS_F, IS_S

The table presents IS_F and IS_S for the full sample for three periods.
The first is the *daily average* of IS_F estimated for the entire period of the trading day. The second is the *First half hour* which shows IS_F estimated for half hour after market open, from 9:55am to 10:30am. The last is *Middle hours* which shows IS_F estimated for the period from 12:00pm to 1:00pm.
The average IC values are also reported as measured for the three distinct periods, all at a transaction size of Rs 250,000.
The numbers in boldface indicate when the average IS_F is significantly different from that for the spot at a 5% level of confidence.

	IS_F			IS_S			IC_F	IC_S
	Max	Min	Mean	Max	Min	Mean	(in %)	
Daily average	0.52	0.46	0.49	0.54	0.48	0.51	0.24	**0.13**
First half hour	0.60	0.53	**0.56**	0.47	0.40	0.44	0.26	0.18
Middle hours	0.52	0.45	0.49	0.55	0.48	0.51	0.19	**0.12**

Price discovery during periods of high market volatility

Prices become volatile when there is a greater information flow in the market. One predictable time of high market volatility is during opening of the market. The trading at the start of the day adjusts prices for overnight news from global markets. This shows consistently as high volatility for a period immediately after market open.[17]

We focus on two periods: (1) *First half hour*: (between 9:55am to 10:30am) half an hour after the open of trading in the market, and (2) *Middle hours* (12:00pm upto 1:00pm).[18] We estimate IS_F for both periods, and report these for the full sample for three periods: the whole trading period, the

[17]Thomas (2010) tests the intraday market index volatility for structural breaks, and finds that there is a spike of volatility immediately at market open. This finding is common to several markets world-wide. The paper also finds that volatility persists for around half an hour after open, on average, indicating that the market takes this time to adjust to the overnight news effect. The paper also documents two other volatility periods: a middle period of low volatility, and a higher volatility period, for an hour before market close.

[18]We also estimated IS for the *Last hour* of the trade (2:30pm upto 3:30pm). However, as it turned out, we did not expect a significant departure of the IS values from the ones estimated for the *Middle hours* period despite the high volatility observed during that time. This was because, unlike the *First half hour* of trading, when market adjust to the overnight news, such is not the case with the *Last hour* of the trade. The results for *Last hour* are available on request.

First half hour and the Middle hours in Table 9.

The results for the full sample show that the futures market plays a dominant role in the first half hour of trading when market volatility is significantly higher. This is different from the role of the futures market when estimated as the average over the entire trading day. This difference is not supported by any clear evidence in the intra-day price impact cost (the last two columns in Table 9) that would indicate that a shift in the liquidity of the futures and spot markets is correlated with the higher dominance of futures prices during these hours.

Instead, the reason for the shift in price discovery to the futures market appear to be driven because of trading response to information flows. When the probability of information flows into the market is higher, the futures contract appear to contribute more to price discovery than they do during periods when the market is calm.[19]

A closer look at the intra-day IS across different liquidity quartiles in Table 10 reveal a consistent behaviour of the futures market in price discovery.[20] Futures dominate spot markets in securities in the first three quartiles by impact cost. Even though, the last quartile of the securities with least futures liquidity still has the spot market dominate price discovery, there is a greater shift in price discovery towards futures than can be observed in the daily average, or during the calm period of the *middle hours* of the trading day.

In summary, we find that the average IS_F increases during the early hours of trading when overnight news causes high volatility in prices. This is found in the average for the full sample, as well as across the first three liquidity quartiles. Without this upsurge of information, IS_F retains the overall daily average character during the middle hours, when there is typically low probability of information arrival. There is little evidence from the intra-day

[19]We apply the IS-CS robustness check using ratio as defined in Equation-1 across the two different periods (*First half an hour* post opening and during *middle hours*). We see that the value of the ratio rises across all quartiles in the first half an hour of trading, lending support to our argument that during periods of high information flow, futures market tends to be the preferred choice of trading. The value of ratio for Q4 securities, still, however remain less than one, indicating that for Q4 stocks wth low liquidity on futures market, spot market remains to be the preferred trading venue. The results are given in Table 13 in the Appendix.

[20]These quartiles have been created by using the impact cost liquidity measure. The results do not change for the traded volume quartiles.

Table 10 Intra-day behaviour of average IS across liquidity quartiles

The table presents the average IS for the futures and spot markets calculated for each of the four quartiles where the securities are classified in order of decreasing liquidity by higher values of price impact cost.
The definitions of *daily average*, *First half hour* and *Middle hours* is the same as those used in Table 9.
The values marked in boldface indicate instances when the average IS_F is significantly different from IS_S at a 5% level.

	IS_F			IS_S			IC_F	IC_S
	Max	Min	Mean	Max	Min	Mean	(in %)	
Q1 (highest liquidity by IC)								
Daily average	0.66	0.55	**0.61**	0.45	0.34	0.39	0.04	0.04
First half hour	0.72	0.61	**0.66**	0.39	0.28	0.34	0.05	0.04
Middle hours	0.65	0.54	**0.59**	0.46	0.35	0.41	0.04	0.04
Q2								
Daily average	0.63	0.55	**0.59**	0.45	0.37	0.41	**0.07**	0.06
First half hour	0.71	0.63	**0.67**	0.37	0.29	0.33	0.07	0.07
Middle hours	0.61	0.54	**0.58**	0.46	0.39	0.42	**0.07**	0.06
Q3								
Daily average	0.55	0.51	0.53	0.49	0.45	0.47	0.13	0.11
First half hour	0.62	0.57	**0.60**	0.43	0.38	0.40	0.14	0.14
Middle hours	0.52	0.48	0.50	0.52	0.48	0.50	0.13	0.13
Q4 (lowest liquidity by IC)								
Daily average	0.25	0.23	0.24	0.77	0.75	**0.76**	**0.74**	0.29
First half hour	0.35	0.30	0.32	0.70	0.65	**0.68**	**0.77**	0.44
Middle hours	0.28	0.26	0.27	0.74	0.72	**0.73**	**0.52**	0.27

patterns in observed impact cost liquidity measures to explain this shift of dominance in price discovery to futures markets. This indicates that traders tend to use futures contracts when there is a higher information flows expected in the market.

Price discovery during periods of security specific volatility

We next examine the behaviour of IS around periods of anticipated security specific information flows. These are identified as days of earnings announcement of the sample securities in the study. Further, we also identify the time during the trading day when the earnings were announced at the exchanges for each security. In this way, we try to estimate the value of the IS_F in the thirty minute period immediately post announcement, in the attempt to pinpoint the process through which prices adjust between the futures and the spot markets. We compare these announcement period IS_F estimates with those of average daily IS_F estimates in order to test our hypothesis that traders tend to use leveraged products more during times of high information flows.

In the sample of the study, there were two periods when earnings announcements were made:

1. Results for the last quarter of FY 2009[21] were announced during Apr/May 2009.
2. Results for the first quarter of FY 2010 for which results were announced during Jul/Aug 2009.

Table 11 IS results for quartiles based on price impact cost

The table reports the average IS_F and IS_S for a 30-minute period just after earnings announcements compared with the averages estimated over the full period. These are reported for the full sample of 97 securities as well as by the quartiles by liquidity (price impact cost).
The values marked in boldface indicate instances when the average IS_F is significantly different from IS_S at a 5% level.

	IS_F			IS_S			IC_F	IC_S
	Max	Min	Mean	Max	Min	Mean		
Full sample								
Announcements	0.57	0.50	**0.54**	0.50	0.43	0.46	**0.22**	0.13
Overall period	0.52	0.46	0.50	0.54	0.48	0.50	**0.24**	0.13
Q1								
Announcements	0.60	0.48	0.54	0.52	0.40	0.46	0.04	0.04
Overall period	0.66	0.55	**0.61**	0.45	0.34	0.39	0.04	0.04
Q2								
Announcements	0.65	0.59	**0.62**	0.41	0.35	0.38	0.07	0.06
Overall period	0.63	0.55	**0.59**	0.45	0.37	0.41	0.07	0.06
Q3								
Announcements	0.56	0.50	0.54	0.50	0.42	0.46	0.12	0.11
Overall period	0.55	0.51	0.53	0.49	0.45	0.47	0.13	0.11
Q4								
Announcements	0.45	0.44	0.44	0.56	0.55	0.56	**0.65**	0.29
Overall period	0.25	0.23	0.24	0.77	0.75	**0.76**	**0.74**	0.29

[21]In India, the financial year (FY) is from Apr 1 - Mar 31

Table 11 presents IS_F averaged for the full sample, as well as across the securities quartiles (by price impact cost) for the announcement days in these two periods. The table also shows the price impact cost values in the half hour after the announcement compared to the price impact cost of the security in the overall sample.

These tables also show higher values of IS_F during the period immediately after securities earnings announcements. As against the full sample average IS_F during the period of high market volatility, the IS_F during the post-announcement period turns out to be the dominating the price discovery process indicating the preference of leveraged product during periods of high news flow in the market. Categorising the results in the order of decreasing liquidity further indicate the futures market dominating price discovery for securities with higher liquidity. There is a shift in the importance of futures across all the quartiles during these earnings announcement periods, even though the spot market still dominates price discovery for the least liquid securities in Q4.

6 Conclusion

This paper re-visits the question of where price discovery takes place between leveraged (single security futures) and non-leveraged (spot) markets. The accepted wisdom is that leverage lowers transactions costs of capital in trading information, because of which SSF markets should dominate spot in the price discovery process. However, the literature has persistently failed to find clear relationships of this nature, other than in the case of index futures.

Some of these papers indicate that there is a shift to a greater role of leveraged contracts when they are liquid. Since all transactions costs critically influence the speculators decision on where to trade when information arrives, the liquidity of the market can be a significant factor affecting where prices get discovered. The lack of liqudity in a leveraged market can be a counterbalance to the positive benefits of leverage, so much so that the trader makes a choice to trade in a liquid spot market rather than an illiquid futures market.

In this paper, we test the role of liquidity against leverage in the price discovery process between futures and spot markets. We use the relatively unique setting of the Indian SSF markets which are cash-settled and are very successful, unlike a lot of other SSF markets globally. We also take advantage of the transparency of the electronic limit order book market structure which allows us to observe standardised measures of pre-trade liquidity, which is the real measure that would influence trading choices between markets.

We estimate the Hasbrouck (1995) information share measure (IS) using high-frequency mid-quote prices for both SSF (IS_F) and spot (IS_S) markets. Like earlier studies on this subject, we find that on average, neither the SSF nor spot markets dominate price discovery, with a full sample average of IS_F=0.49 and IS_S=0.51.

However, when we categorise securities by liquidity, the IS_F have average values significantly higher than 0.5 for the more liquid securities, which have higher futures market liquidity relative to spot market liquidity. In contrast, the IS_F become significantly less than 0.50 for securities where the futures market liquidity drops relative to spot market liquidity.

We find these results are consistent regardless of whether we sort the securities by post-trade liquidity measures (traded volumes) or pre-trade measures (price impact cost). We also find that the IS_F estimates are more robust when the futures markets have higher liquidity relative to the spot markets. When the ratio of price impact of the futures market to spot market is less than one, there is a strong and consistent dominance of futures in price discovery. This provides strong evidence of the importance of liquidity costs in driving price discovery.

Lastly, we test for the importance of liquidity in instances when there is a strong flow of information into the market. During such periods, traders would automatically prefer futures contracts for the higher returns with leverage. While we find that the role of futures market does go up, liquidity still acts to bind the dominance of the futures in price discovery compared to the spot market.

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7 Appendix

Table 12 Characteristics for quartiles by price impact cost

The original sample of 97 securities are broken into quartiles Q1−Q4 by traded volumes. Q1 is the quartile with the most liquid securities, or those with the lowest impact cost during the sample period. Q4 is the set of securities with the least liquidity or highest impact cost.
The measures presented below has been calculated similar to those in Table 2. The numbers in boldface are where the futures markets values are significantly different from the spot market values at a 5% confidence level.

	Q1		Q2		Q3		Q4	
	Futures	Spot	Futures	Spot	Futures	Spot	Futures	Spot
Volumes ('000 shares)	9707	7846	9529	8405	5337	3940	634	770
Spread (%)	**0.11**	0.05	**0.15**	0.07	**0.28**	0.11	**1.74**	0.23
IC (%)	**0.04**	0.04	**0.07**	0.06	**0.13**	0.11	**0.74**	0.29
$\Delta IC_{\text{(Futures - Spot)}}$								
σ_{IC} (%)	0.45	0.54	0.75	0.83	**1.61**	1.63	**9.68**	5.14
σ_{returns} (%)	50	49	54	53	52	51	52	48

Table 13 IS and CS results based on IC quartiles

The numbers in the table indicate the average daily IS (Mean of upper bound and lower bound) and CS value for the full sample as well as across impact cost quartiles. The last column uses the IS and CS collectively to determine which market is more responsive to the permanent shocks.
The numbers in boldface indicate when the ratio is significantly greater than one at the 5% level of significance.

	IS$_F$	IS$_S$	CS$_F$	CS$_S$	$\frac{\lvert IS_F \times CS_S \rvert}{\lvert IS_S \times CS_F \rvert}$
Q1 (highest liquidity by IC)					
Daily average	0.61	0.39	0.58	0.42	**1.14**
First half hour	0.66	0.34	0.62	0.38	**1.24**
Middle hours	0.59	0.41	0.57	0.43	**1.11**
Q2					
Daily average	0.59	0.41	0.56	0.44	**1.13**
First half hour	0.67	0.33	0.61	0.39	**1.30**
Middle hours	0.58	0.42	0.55	0.45	**1.13**
Q3					
Daily average	0.53	0.47	0.52	0.48	1.06
First half hour	0.60	0.40	0.56	0.44	**1.16**
Middle hours	0.50	0.50	0.49	0.51	1.02
Q4 (lowest liquidity by IC)					
Daily average	0.24	0.76	0.32	0.68	0.68
First half hour	0.32	0.68	0.38	0.62	0.77
Middle hours	0.27	0.73	0.34	0.66	0.69